ESSAYS ON CONSUMER SHOPPING BEHAVIOR OVER THE BUSINESS CYCLE AND WAGE INCOME SMOOTHING

A Dissertation

Presented to

The Faculty of the Department

of Economics

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Doctor of Philosophy

By

Wen Long

May 2015

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Abstract

The first chapter consists of two essays. The first essay studies if and how consumers search for low prices (bargains). Using a panel of prices and quantities of consumer purchases measured at the UPC-level, I find that consumers paid lower prices after the Great Recession which is interpreted as an outcome of increased search intensity. There is large heterogeneity among consumers. I categorize consumers, by year, into three types by the degree of search intensity: bargain hunters, average consumers, and inattentive shoppers and find that consumer types are not very persistent. Further,I find that consumers rationally search for lower prices for product categories of which they consume a lot while they search less for lower prices for products they consume less of. I write a simple model of shopping time allocation for two goods which rationalizes that consumers will search more intensively for lower prices on the good on which they spends more. In addition, we find evidence that in the recession consumers pay more shopping trips and visit more stores to search for bargains. In the second essay, Adopting the framework of Asdrubali, Sorensen and Yosha (1996), I identity three channels of wage income smoothing: net taxes, employers, and interstate commuting income. They smooth 1.8%, 55.1% and 3.0%, respectively, of shocks to Gross State Product (GSP). 40.1% of shocks are not smoothed. I split the sample into four non-overlapping time periods and find the shares of net taxes on production and employers change significantly over time. Lastly, I test the asymmetry of wage income smoothing over the business cycle. The responses of wage incomes to GSP shocks exhibit a reversed "rockets and feathers" feature, i.e. wage incomes respond stronger and faster to negative shocks than positive shocks.

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to

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Chapter 1

Heterogeneous Consumer Shopping Behavior: Evidence from Retail Scanner Data

1.1 Introduction

How do heterogeneous consumers shop? A consumer can increase his or her search intensity by spending more time on shopping and thereby lowering expenditure in different ways: buying during sales, using coupons, and switching to generic brand products. Since the seminal work by Aguiar and Hurst (2005), it has been well known that consumers with certain demographic characteristics, such as retirement and non-employment, pay lower prices than others.

It would be interesting to further exploit heterogeneity in consumer shopping behavior and its evolution over the business cycle. Does a consumer's search intensity respond to the business cycle? If so, is there a difference in the response across consumers grouped by demographic characteristics? Does a consumer have a consistent level of search intensity over all goods she buys? To shed light on these issues, we conduct a systematic study of heterogeneity in consumer shopping behavior using data from the IRI Academic Data Set, which contains 11 years of weekly store data for 30 grocery categories and panel data of household purchase transactions in two pilot markets, Pittsfield, Massachusetts and Eau Claire, Wisconsin. Complementary to Aguiar and Hurst (2005), we find large heterogeneity of search intensity within each age group and across products.

Our work is also one of the first papers studying the business cycle aspect of bargain hunting. The existing literature is mostly cross-sectional and do not explore the business cycle dimension of consumption using retail scanner data. A notable exception is Nevo and Wong (2014), to which our paper is closely related. They also find that households across demographic groups change their shopping behaviors during the Great Recession.

We start by constructing a bargain hunting index (BHI) as a measure of search intensity. For each household, we compute BHI by comparing the expenditure they pay for their consumption bundle, to the hypothetical expenditure of the same bundle if "average" market prices were paid instead. We categorize households into three types. A household is defined as a bargain hunter in a year if the BHI lies in the bottom quartile, an inattentive shopper if the BHI in the top quartile, or an average consumer if the BHI in the other two quartiles. We also calculate the BHI for each product category and define a consumer type for all product categories that a household purchases.

We regress the household BHI on demographic variables and city unemployment rates over the period from 2001 to 2011. Consistent with the literature (Aguiar and Hurst (2007), Kaplan and Menzio (2014)), we find that households who are older, have non-employed members and lower incomes pay lower prices. In addition, during the Great Recession, households increased their search intensity. Similar to Nevo and Wong (2014), we also find households exposing to different levels of income shocks changed their search intensity to varying extent. Specifically, households whose head was in retirement did not increase their search intensity as much as others, while those whose head is non-employed increased their search intensity even more than others.

Another contribution to the literature is a deepening understanding of time allocation in the home production model (Benhabib, Rogerson and Wright (1991) and

Greenwood and Hercowitz (1991)). When there is a negative income shock, individuals substitute between time and market goods, and then smooth their consumption by spending more time on shopping to lower the effective price they pay. We study the intratemporal allocation of shopping time at a more granular level—between product categories. A household is more likely being a bargain hunter and less likely being an inattentive shopper for a product category on which she spends more. This finding suggests consumers do not evenly allocate their search effort and instead devote more search effort to product categories on which they spend more. We also find that after the Great Recession, on average households became bargain hunters for more product categories and inattentive shoppers for fewer categories.

The rest of the paper is organized as follows. Section 2 reviews the literature while Section 3 describes the data. In Section 4, we display the shape of the bargain hunting index and study heterogeneity in bargain hunting across demographic groups. In Section 5, we present the determinants of bargain hunting and the effect of income shocks and, in Section 6, we show the concentration of savings from bargain hunting. Section 7 is the conclusion.

1.2 Literature Review

This paper is closely related to Nevo and Wong (2014). They find that changes in shopping patterns occur over the business cycle. Households across demographic groups purchase more sale items, use more coupons, buy more generic products and large sized items, and spend a larger share of expenditure on Big Box stores, all of which contributes to lower effective prices paid by households, during the Great Recession. Continuing this direction of research, we also find that the local unemployment rate is a determinant of bargain hunting. During the Great Recession, households whose heads are non-employed and thus having more difficulty in coming back to employment pay 0.36 percent less than households whose heads are employed, in response to an 1% increase in the local unemployment rate.

Our work relates to various strands of the literature on consumer shopping behavior and self-insurance. First, our work relates to recent studies on opportunity cost of time over the business cycle. Aside from formal savings and public insurance, households can also smooth unanticipated income shocks by spending more time on shopping when the opportunity cost of time is low in a recession. Nevo and Wong (2014) find that households' opportunity cost of time declined by 25-30 percent over 2008-2010. Aguiar, Hurst and Karabarbounis (2013) show that around 30 percent of the lost labor hours are reallocated toward non-market work, including shopping, during the Great Recession. Our work quantifies the amount of change in the decrease of bargain hunting index, the consequence of increased shopping time and efforts by consumers, in the Great Recession.

Second, our study of shopping activities adds to the literature of inattentive consumers. Reis (2006) studies the consumption decisions of agents who face costs of acquiring, absorbing and processing information. With such costs, consumers rationally update their consumption plans only occasionally which implies a slow adjustment of consumption to news. In his model, individual consumption is sensitive to ordinary and unexpected past news, but not to extraordinary or predictable events as it pays to reconsider consumption plans when the economic circumstances change substantially. Our work gives direct empirical evidence for the theory of rational inattentive consumers. Households who spend more on a product category are less likely to be inattentive consumers of that category.

Third, our paper complements studies on consumer heterogeneity. Chevalier and Kashyap (2011) posit a model with two types of consumers, (1) loyals who stick to their preferred brands and do not time their purchases and (2) shoppers who pay the best price possible as they chase discounts, substitute across brands and/or stockpile products during sales. Our results provide further evidence of this model. Bargain hunters and inattentive consumers, as defined in our data, correspond to ”shoppers” and ”loyals” in their model. They indeed display different shopping behaviors and the difference between two groups of average price indexes change over the business cycle.

Fourth, several influential papers (Diamond 1971, Bils and Klenow 2004, and Nakamura and Steinsson 2011) have studied the frequency of price adjustments using micro-level price data. Price setting has important implications for a variety of issues in macroeconomics such as optimal monetary policy design or the welfare costs of business cycles. Our work is closely related to Coibion, Gorodnichenko and Hong (2015) (hereafter CGH 2015), who investigate to what extent the prices “posted” by retailers differ from the “effective” (or actual) prices paid by households. Substitution bias (buying less expensive goods) and the reallocation of expenditures across stores (switching to cheaper stores) by households are two distinct mechanisms which could drive down the cost of consumers' baskets during recessions, opening a wedge between both prices. CGH (2015) document that actual prices are more flexible than posted prices and that sales are pro-cyclical—sales are both less frequent and less sizable when unemployment rates are high. The authors argue that store switching can account for both facts, the wedge between both prices and the pro-cyclicality of sales. High-price retailers might have less incentives to initiate sales during recessions when households have more incentives to search for bargains at low-price retailers instead (time-varying searching effort). Store switching can drive a wedge between posted and effective prices at the individual product level. We use the same dataset as CGH (2015), very detailed supermarket transaction records collected by IRI, but unlike the previous study we have data for the period of the Great Recession while CGH (2015) focus on the years 2001–2007.

The Great Recession certainly qualifies as an extraordinary event that should have focused the attention of many consumers at the same time. It is only natural to ask if the fraction of inattentive consumers varies over the business cycle, or if loyals are more likely to become shoppers in such situations. As Aguiar, Hurst and Karabarbounis (2013) document, time-use allocations change during recessions. In the last recession, home production absorbed about 30 percent of foregone market work hours (the rest going to leisure and other activities). Of that 30 percent, 7 percent represents increases in shopping time, 15 percent goes to core home production (cooking, cleaning, laundry, etc.) while the rest goes to home maintenance and repairs, and caring for other older adults. Aguiar and Hurst (2007) show that households can and do alter the relationship between consumption and expenditure by changing time inputs. In fact, older individuals pay less for the same products because they spend more time shopping and are more likely to use discounts. Unlike Aguiar and Hurst (2007), who focus on the relationship between consumption and expenditure over the life cycle, our focus is on the business cycle.

1.3 Data Description

1.3.1 IRI Academic Data Set

In this paper we use the IRI academic data set, which has very detailed information on grocery purchases over 2001-2011 in 31 categories from 50 markets (each roughly corresponding to a Metropolitan Statistical Area (MSA)). Transaction prices and quantities are collected both at the store level and the individual transaction level. The data set is described in details in Bronnerberg et al.(2008).

At the store level, weekly total sales and quantity data for each UPC (Universal Product Code) are collected for stores in all 50 markets. A UPC is the barcode used for scanning at the point of sales. Information of the transaction including the price and quantity of each product bought by the consumer is transmitted to the retailer's database. There are two types of stores in the data: grocery stores and drug stores. Many stores are chains of the same retailer, but each store has a unique identifier and chain number, from which we can track the weekly revenue and quantity for every UPC sold in the store over time. Retailers (or chains of retailers) cannot be identified by name.

At the individual transaction level, the household panel records prices and quantities for all transactions made by households in two small metropolitan areas: Eau

Claire, Wisconsin and Pittsfield, Massachusetts. Every entry in the household panel is a transaction of a product, narrowly defined by the UPC, made by a household at a particular time. We also know certain household characteristics: household heads' age, race, marital status, education, employment status, occupation, family size, household income and home ownership. All these variables are categorical variables.

The data set contains rich information on product attributes such as volume, pack size, brand name, producer, and flavor and scent for some products. Take a milk product as an example. For a product with the UPC "00-01-20742-00303", from the data set we know its brand name is "New Square," produced by the company "Ahava Food", and with a volume of 32 oz. We also know it is fat-free skim milk with Vitamin A&D additives, white color, packaged in a plastic jug and is pasteurized homogenized. Note that products that are essentially the same but only differ in size have different UPCs and thus are considered a different product. For instance, a 12-pack Pepsi Coke has a different UPC from a 6-pack Pepsi Coke, and price and quantity data for them have separate entries.

The household panel in the IRI Academic Data Set has advantages and disadvantages comparing to two other well-known consumption data sets: Panel Study of Income Dynamics (PSID) and Consumer Expenditure Survey (CEX). The PSID and the CEX collect data on expenditure on food purchase, while the household panel in the IRI academic data set has prices and quantities, including the exact products they buy (at the UPC level), the exact stores, and the exact time (up to the exact week in 2001-2007 and up to the exact minute in 2008–2011). This advantage helps us better understand the composition in a consumer's consumption bundles and their shopping behavior at finer product categories. An obvious drawback is the household panel covers just two small MSAs, and the sample is not nationally representative.

Two other retail scanner data sets used in the literature are ACNielsen's Homescan Panel(Aguiar and Hurst (2007), Hausman and Leibtag (2007), Kaplan and Mezio (2013)) and the TNS Worldpanel for Great Britain (Griffith, Leibtag, Leicester and Nevo 2009). Only individual purchase records, but not store level data, are available in these two data sets. One advantage of the ACNielsen's panel is that it contains direct information regarding discounts from coupons and sales, while in the IRI academic data set, temporary price reductions (promotions or sales) are flagged as a binary variable, which equals one if the temporary price reduction is 5% or greater. Because regular prices are not available when the product is on sale, discounts from sales can only be inferred by comparing the reduced price to previous regular prices. In the household panel such flag variables do not exist. We only observe the actual price a household pays but not the regular prices or whether a product is on sale or not.

In this paper, we focus on the the household panel data because our research interest is consumption smoothing by households. For male household heads, the age distribution is 10 percent below 45, 25 percent aged 45–54, 21.7 percent aged 55–64, 22 percent over 65, and 21 percent unclassified. In terms of household income, 12.5 percent have income under \$20,000; 20.3 percent earn \$20,000–\$35,000, 27.4 percent earn \$35,000–\$55,000, 19.2 percent earn \$55,000–\$75,000, 12.7 percent have \$75,000–\$100,000, and 7.8 percent over \$100,000. For education, 35.7 percent of heads have high school or less education and 18.9 percent have graduated from college or higher.

As a summary, the sample is older and less educated than a typical sample from the PSID.

1.3.2 Definition a Good

Kaplan and Menzio (2014) propose four definitions of a good at different levels from narrowest to broadest: UPC, generic brand aggregation, brand aggregation, and brand and size aggregation. Throughout the paper, we define a good by its UPC. Goods within the same product categories but with different UPCs are considered different goods. For example, an one litre Coca Cola soda is a different good from a two litres Coca Cola soda. An one litre Coca Cola is a different good from an one litre Pepsi soda.

1.3.3 Definition of the Average Price

Aguiar and Hurst (2007) define the average price of product as the average price paid by households for a particular good j (at a UPC level) in a particular time t as

$$\overline{p_{j,t}} = \sum\nolimits_{i,t} \left(\frac{q_{i,j,t}}{\sum_{i,t} q_{i,j,t}} \right) p_{i,j,t} \quad ,$$

where i denotes a household. The average price of a good is a quantity-weighted average of individual transactions of the good j in time t, which is a month in a year.

We define the average price of a good as the simple average of prices posted by all stores in a market m in a week k as

$$\overline{p_{j,m,k}} = \frac{1}{N} \sum_{s=1}^{N} p_{j,s,m,k} \quad ,$$

where s is a store, and N is the total number of stores in a market. The store-posted price is defined as weekly sale revenue of good j over the quantity of the product sold in a store in a week:

$$p_{j,s,m,k} = \frac{Rev_{j,s,m,k}}{q_{j,s,m,k}} \quad ,$$

where Rev is the weekly sale revenue from good j.

For our research objective, this definition has several advantages. This measure gives equal weight to each store and reflect the expected price for a consumer who walks into a randomly selected store. Second, our definition reduces the measurement errors of the average prices for goods with few transactions. Even there is only one transaction of the good in a store in a week, it is the still exact price charged by the store. Note that a store sales discount apply to all buyers, and discounts from manufacture coupons do not affect the revenue of a product, even though it does reduce the final bill for a household, since the retailer gets reimbursement from the manufacture who is the coupon issuer.

1.3.4 Definition of the Bargain Hunting Index

The bargain hunting index (BHI) is defined as:

$$BHI_{i,m,t} = \frac{Actual\ Exp_{i,m,t}}{Hypo\ Exp_{i,m,t}} - 1 = \frac{\sum_{j,k} P_{i,j,m,k} * Q_{i,j,m,k}}{\sum_{j,k} \overline{P_{j,m,k}} * Q_{i,j,m,k}} - 1 \quad ,$$

where i is a household, m is one of the two cities (Eau Claire, WI or Pittsfield, MA),t is a quarter or a year, j is a good, and k is a week. For each transaction of a good by a household in a week, we find the exact prices of the product (identified by its UPC) in all stores in the city the households resides in the same week. Hypothetical expenditure is measured using the average store-posted price ($\overline{P_{mk}}$) of the good in the same week in the same city, given the consumer's own consumption bundle. Expenditure is aggregated over a quarter or a year. A lower BHI means paying less relative to the store-posted prices given the household's consumption bundle, which reflects higher shopping intensity.

1.3.5 Three Types of Consumers

We categorize households into three types: bargain hunters, average consumers and inattentive shoppers. We first rank the BHI of all households in a city m in a time period t (a year or a quarter) from low to high. Households in the bottom quartile are labeled "bargain hunter", those in the top quartile "inattentive shoppers", and the rest "average consumers".

1.4 Dispersion of Bargain Hunting Index

We start by graphically display the dispersion of BHI for the year 2011 in Figure 1. A typical distribution of bargain hunting index is right-skewed and leptokurtic. More than 50% of consumers in each sub-sample pay less than the store-posted prices. This reflects the fact that a larger share of household heads in the sample are more than 55, and older individuals are prone to be bargain hunters (Aguiar and Hurst 2005, 2007).

In Figure 1, we split the sample into two, age of household heads over 60 and under 60, and plot their histograms of bargain hunting index separately. The shape of the BHI distribution in each age group is very similar. Two findings are interesting. First, there is a wide dispersion of BHI within each age group. Among the households whose heads aging more than 60, some of them shop less intensively and pay 30% more than others, holding their own consumption bundles. Second, the relative position of the two histograms explains the well known fact in the literature - older consumers pay less than younger one. The histogram for older households is close to a leftward parallel shifting of the histogram for younger households with higher kurtosis. In other words, an average older consumer pay less than an average younger consumer. However, an older inattentive shopper pay more than a younger bargain hunter.

1.5 Change of Bargain Hunting Index over the Business Cycle

The section examines the effect of income shocks on households' BHI. Ideally, we would like to know the response of households to negative shocks such as job loss. However, certain household characteristics such as employment status are surveyed only three times (twice in 2007, once in 2012), not in every year. Consequently, most of the variation in household characteristics is cross-sectional, with limited intertemporal variation. We use data from the 2007 survey for the 2001–2007 data and data from the 2012 survey for the 2008–2012 data. We supplement the household panel data with MSA-level unemployment rates for these two cities as a measure of city-wide shocks. We use monthly unemployment rates from the Bureau of Labor Statistics (BLS). Quarterly unemployment rates are the mean of three monthly rates in the quarter.

We regress the BHI index on indicators of time available for shopping; namely, employment status, the unemployment rate in the city (as a proxy for household head unemployment which is not observed) and year and household fixed effects. The results, reported in Table 1, are that wealthier households pay more (consistent with a higher value of time in formal employment), retirees and other non-employed pay less (although those coefficients are not significant and typical significance levels) and household pay less relative to the store average, with very high statistical significance, when unemployment is high.

1.6 Bargain Hunting Index by Product Category

1.6.1 Definition

We now turn to a finer definition of BHI. We ask whether a consumer can be a bargain hunter for a product category and in the meanwhile an inattentive shopper for another category. To our knowledge, there is no existing study of the relative shopping intensity across goods.

Similar to the definition of BHI for total expenditure, the definition of BHI for a product category is:

$$BHI_{i,c,m,t} = \frac{Actual\ Exp_{i,c,m,t}}{Hypo\ Exp_{i,c,m,t}} - 1 = \frac{\sum_{j,k} P_{i,j,m,k} * Q_{i,j,m,k}}{\sum_{j,k} \overline{P_{j,m,k}} * Q_{i,j,m,k}} - 1$$

where i is a household, c is a product category, j is a good in the product category c, m is one of the two cities (Eau Claire, WI or Pittsfield, MA),t is a year, k is a week.

Again, we categorize a household into three types of consumers by the order of their BHI for a product category from low to high. A household is a bargain hunter for a category if their BHI lies in the bottom quartile, an inattentive consumer if in the top quartile, and an average consumer for the rest.

We find there is a wide dispersion of BHI across product categories. A household is found to be bargain hunters of some categories and inattentive or average consumers for other categories.

Figure 2 illustrates the average number of product categories for which a household is a(n) bargain hunter/inattentive shopper over time. To obtain the average number, we first label the type of consumer for every household and all product categories in every year. Now each household has the number of categories for which they are a(n) bargain hunter/average consumer/inattentive consumer. We calculate the average number for each type across all households in a city in a year. Then we take the average across the two cities and plot Figure 2.

Over the business cycle, we see households respond to the overall economic condition by adjusting their overall shopping intensity. During the Great Recession, there is a clear departure in the pattern from that during the boom year from 2003 to 2007. On average, households became bargain hunters in more categories and inattentive shoppers in fewer categories.

1.6.2 A Model of Shopping Time Allocation over Products

Here we develop a simple model, in the spirit of Becker (1961), to study the allocation of shopping time over two goods.

The objective function:

$$max\ U = \alpha lnC_1 + (1-\alpha)lnC_2 - \mu(T_1 + T_2) \tag{1.1}$$

subject to two constraints:

$$T_1 + T_2 = T$$

$$P_1(T_1)C_1 + P_2(T_2)C_2 = Y$$

C_1 and C_2 are the purchased quantities of good 1 and good 2. μ is the opportunity cost of time. We assume the price of a good is a concave function of shopping time devoted to the good.

Set up the Lagrangian equation:

$$\alpha lnC_1 + (1-\alpha)lnC_2 - \mu(T_1 + T_2) + \lambda(Y - P_1C_1 - P_2C_2)$$

The first order conditions:

$$\alpha\frac{1}{C_1} = \lambda P_1 \tag{1.2}$$

$$(1-\alpha)\frac{1}{C_2} = \lambda P_2 \tag{1.3}$$

Divide (2) by (3),

$$\frac{\alpha}{1-\alpha}\frac{C_2}{C_1} = \frac{P_1}{P_2} \tag{1.4}$$

The first order conditions for T_1 and T_2:

$$-C_1\frac{\partial P_1}{\partial T_1} = -C_2\frac{\partial P_2}{\partial T_2} = \frac{\mu}{\lambda} \tag{1.5}$$

At the equilibrium, one extra hour of shopping time spent on good 1 or good 2 should bring the same amount of savings, which is equal to the opportunity cost of time. Rearrange terms, we have

$$\frac{C_2}{C_1} = \frac{\frac{\partial P_1}{\partial T_1}}{\frac{\partial P_2}{\partial P_1}}\frac{\alpha}{1-\alpha} \tag{1.6}$$

Combine (4) and (6), we have

$$\frac{\frac{\partial P_1}{\partial T_1}}{\frac{\partial P_2}{\partial P_1}}\frac{\alpha}{1-\alpha} = \frac{P_1(T_1)}{P_2(T_2)} \tag{1.7}$$

and then

$$\alpha P_2(T_2)\frac{\partial P_1}{\partial T_1} = (1-\alpha)P_1(T_1)\frac{\partial P_2}{\partial T_2} \tag{1.8}$$

Take the partial derivative with respect to α on both sides.

$$P_2\frac{\partial P_1}{\partial T_1} + \alpha(P_2\frac{\partial^2 P_1}{\partial T_1^2} - \frac{\partial P_1}{\partial T_1}\frac{\partial P_2}{\partial T_2})\frac{\partial T_1}{\partial \alpha} = -P_2\frac{\partial P_2}{\partial T_2} + (1-\alpha)(\frac{\partial P_1}{\partial T_1}\frac{\partial P_2}{\partial T_2} - p_1\frac{\partial^2 P_2}{\partial T_2^2}) \tag{1.9}$$

So the marginal effect of expenditure share of good 1 on the shopping time spent on good 1:

$$\frac{\partial T_1}{\partial \alpha} = \frac{-P_1\frac{\partial P_2}{\partial T_2} - P_2\frac{\partial P_1}{\partial T_1}}{\alpha P_2\frac{\partial^2 P_1}{\partial T_1^2} + (1-\alpha)P_1\frac{\partial^2 P_2}{\partial T_2^2} - \frac{\partial P_1}{\partial T_1}\frac{\partial P_2}{\partial T_2}} \tag{1.10}$$

The numerator on the right hand side is positive. If the denominator is positive, then the marginal effect of expenditure share on shopping time is positive. In the data, we do not observe the actual time allocation by households over goods. Therefore we use BHI for a product category as a proxy for the shopping time, as more shopping time translates into lower prices and thus lower BHI.

1.6.3 Evidence

In Table 2, we explore whether consumers obtain better prices for product categories in which they spend more. We find fairly weak results when consumer fixed effects are not included. This is reflects that wealthier households are likely to have higher expenditure across all categories on average, while such household likely choose to search less for low prices. When we control for household fixed effect, removing interpersonal comparisons and isolating whether a given household search relatively more for low prices for goods consumer more, we find that this is so with very high statistical significance.

1.7 Results

1.7.1 Cyclicality of the Effective Inflation Rate

To assess the cyclicality of the effective inflation rate, relative to the overall inflation rate, as a function of the local unemployment rate, we replicate the baseline regression of CGH (2015) using household level scanner data instead of store level data, which they use. We estimate the regression equation

$$\pi_{mct} = \beta \mathrm{UR}_{mt} + \theta_c + \text{year dummies} + \text{error}\,,$$

where m indexes markets (Eau Claire or Pittsfield), c indexes the product category (e.g., beer, coffee) and t stands for month, respectively. π_{mct} is the effective inflate rate in city m for product c in period t, UR_{mt} is the local monthly unemployment rate, and θ_c denotes category fixed effects. Prices are deflated by monthly CPIs prior to construction of the effective inflation rate. The dependent variable is the effective inflation rate net of inflation based on changes in CPI. For example, if the inflation measured by changes in CPI is 5% and inflation measured by changes in actual prices consumers pay is 3%, then the effective inflation rate is –2%. Details of computing category level effective inflation are in the footnotes of Table 1. The null hypothesis is that the response of the effective inflation rate to a change in local unemployment is the same as that of the regular inflation rate as measured by changes in CPI; i.e. $\beta = 0$. The estimate of β in Table 1 shows that a 1% increase in the local unemployment rate is associated with a 0.28% reduction in the effective inflation rate relative to the regular inflation based on changes in the CPI. The estimate is close to the estimate of 0.25% found in CGH (2015). It implies that consumers are able to substitute for less expensive brands, or find better prices on identical brands, more often during spells of unemployment. The effect is minor, partly because the coefficient is likely biased towards zero if interpreted as the effect of individual-level unemployment, which varies significantly more than the regional average, so the effect may well be important for many unemployed individuals.[1]

1.7.2 Consumer Savings

To measure an upper bound of consumer savings for each UPC in a given month, we use the highest price paid in a market as the benchmark price and calculate the hypothetical expenditure for each household given that household's consumption

[1] We will attempt to correct for this bias in the future.

bundle. The hypothetical expenditure is calculated as

$$\sum_j \bar{p}_{jt} q_{ijt} \,,$$

where q_{ijt} is household i's consumption of good j in month t, and $\bar{p}_{jt}$ is the highest price, across all consumers, paid for this product in a month. The hypothetical expenditure measures how much a household would pay for its consumption bundle if it paid the highest price. The "savings" index, $index_{imt}$,

$$index_{imt} = 100 \left(\frac{\sum_j p_{ijt} q_{ijt}}{\sum_j \bar{p}_{jt} q_{ijt}} - 1 \right) \%$$

measures how much a household has "saved" with its actual expenditure relative to the hypothetical expenditure. To test the cyclicality of saving, we use the following specification:

$$index_{imt} = \beta \mathrm{UR}_{mt} + \gamma X_{imt} + \text{year dummies} + \theta_i + \text{error},$$

where i indexes a household and the dependent variable is the relative saving index, measured by percentage deviation of actual expenditure from hypothetical expenditure. a lower value of $index_{imt}$ measures greater relative savings by that household. X_{imt} is a set of household characteristics including the head's age, education, family size, and combined household income. The results, shown in Table 2, imply that when the local unemployment rate increases by 1%, the distance of household actual expenditure from the expenditure on the same basket of goods evaluated at the highest prices increases by 1.26%.

1.7.2.1 Alternative Specification

To better illustrate the idea of savings relative to hypothetical expenditures, we use the following specification:

$$\log expense_{imt} = \beta_1 \text{UR}_{mt} + \beta_2 \log \overline{expense}_{imt} + \gamma X_{imt} + \text{year dummies} + \theta_i + \text{error}.$$

The dependent variable is a household's actual expenditure. On the right hand side, $\log \overline{expense}_{imt}$ is the hypothetical expenditure at highest prices given a household's consumption bundle. This specification is very similar to that of the previous specification, but has an easier interpretation: holding hypothetical expenditure constant, when the local unemployment rate increases, does a household spend less on its consumption bundle? The results are reported in Table 3. With an 1% increase in the local unemployment rate, holding hypothetical expenditure constant, a household's actual expenditure decreases by 2.7%; i.e., they save more relative to hypothetical expenditure.

1.7.2.2 Number of Stores Visited and Number of Shopping Trips

So far we have not attempted to identify the channels through which consumers save. Griffith, Leibtag, Leicester and Nevo (2009) summarize four channels: purchasing on sale, buying in bulk (at lower per unit prices), buying generic brands, and choosing outlets. We are able to explore the channel of purchasing on sale and choosing outlets. If, in a recession, consumers spend more time looking for deals and/or switch to cheaper outlets, then they would take more trips to stores but visit less stores because they are less likely to visit expensive outlets. To test the cyclicality of the number of stores visited, we use the following specification:

$$\log Nstores_{imt} = \beta \text{UR}_{mt} + \gamma X_{imt} + \text{year dummies} + \theta_i + \text{error},$$

where the dependent variable N_{imt} is the number of stores visited by household i in month t. Results are shown in Table 4. The results imply that when the local unemployment rate increases by 1%, the number of stores visited increases by 1.25%.

To calculate the number of shopping trips, we need the exact time the customer checks out. A transaction with products checked out at a given time (measured to the minute) is counted as one trip. The exact minute of transactions are only available from 2008 to 2011. As noted in the data description section, because households are surveyed only once during this period, there is no time variation of household characteristics over time and they will be absorbed into the household fixed effects. We estimate the following specification for 2008–2011:

$$\log Ntrips_{imt} = \beta \text{UR}_{mt} + \text{year dummies} + \theta_i + \text{error},$$

The results are shown in Table 5 and imply that a 1% increase in the local unemployment rate is associated with 3.27% more shopping trips.

In Table 3, we return to interpersonal comparisons and the main focus is on the second column in which category*year fixed effects are included. Some categories of goods tend to have many sales and whoever consumes a lot of that good may fairly randomly appear to be a high-intensity searcher. Such a pattern is consistent with the first column, which does not control for category*year effects, and the more interesting results are in the second column which does control for category*year effects. This column revels significant differences between households; in particular, households which consume relatively more of a category search more for low prices and old household search more. Retirement is also significant, with more search, even after controlling for age, and unemployment is significant with a very large t-value over 60.

1.8 Conclusion

In this paper, we study the heterogeneity in consumers' shopping behavior. First, there is considerable amount of heterogeneity in search intensity for lower prices by households across and within every age group. On average, older consumers pay less for their consumption bundle than younger consumers. However, inattentive shoppers pay 30% more than bargain hunters within the same age group.Second, consumers search harder in a recession. An 1% increase in the local unemployment rate increases the search intensity by 0.25%. Household receiving different levels of income shocks display varying search intensity. Third, we categorize consumers into three types by the order of search intensity: bargain hunters, average consumers and inattentive shoppers. We then examine shopping behavior at the product category level. An interesting finding is that the consumer types do not persist over the business cycle. During the Great Recession, on average consumers became bargain hunters of more product categories and inattentive shoppers of fewer categories. Lastly, we write a simple model to study the shopping time allocation, an extension of home production models. We find that consumers more likely to be a bargain bargain hunter and less likely to be an inattentive shopper for a product category on which they spend more.

It would be interesting to examine heterogeneity in consumers' shopping behavior at an even finer level, i.e. at the UPC level. Do consumers rationalize their shopping time over goods within the same category? For example, if a consumer is a bargain hunter of carbonated beverage, is it possible she is a bargain hunter of Pepsi but an inattentive shopper of Coca Cola, a bargain hunter of 2 litre coke and inattentive shopper of 1 litre coke? There is need for more research in this field.

Table 1.1: Product Categories

Beer	Household Cleaner	Salt Snack
Blades	Hot Dog	Shampoo
Carbonated Beverages	Laundry Detergent	Soup
Cigarettes	Margarine/Butter	Spaghetti Sauce
Coffee	Mayo	Toilet Tissue
Cold Cereals	Milk	Tooth Brush
Deodorant	Mustard/Ketchup	Tooth Paste
Diapers	Paper Towel	Yogurt
Facial Tissue	Peanut Butter	
Frozen Dinner	Photo	
Frozen Pizza	Razors	

Notes: There are a few product categories that have relatively very few observations, so that we do not include them in any of the regressions. These categories are blades, cigarettes, hot dog, photo, razors, and soup.

Table 1.2: IRI Markets

Atlanta	Knoxville	Richmond/Norfok
Birmingham/Montgomery	Los Angeles	Roanoke
Buffalo/Rochester	Milwaukee	Sacramento
Charlotte	Minneapolis/St Paul	Salt Lake City
Chicago	MIssissippi	San Diego
Cleveland	New England	San Francisco
Dallas, TX	New Orleans, LA	Seattle/Tacoma
Des Moines	New York City	South Carolina
Detroit	Oklahoma City	Spokane
Eau Claire	Omaha	St. Louis
Grand Rapids	Peoria/Springfield	Syracuse
Green Bay	Philadelphia	Toledo
Harrisburg/Scrant	Phoenix, AZ	Tulsa, OK
Hartford	Pittsfield	Washington, DC
Houston	Portland, OR	West Texas/New Mexico
Indianapolis	Providnce, RI	
Kansas City	Raleigh/Durham	

Notes: There are 50 IRI markets included. Pittsfield and Eau Claire are the only two BehaviorScan markets with household panel data. Other 48 standard markets have store level data only. Monthly seasonally-adjusted unemployment rates data are from Bureau of Labor Statistics. If the IRI market is two metropolitan areas combined, we use the average of the two unemployment rates for this market. If the IRI market is a state, we use the state level unemployment rate. In the special case of the IRI market "West Texas/New Mexico", we just use unemployment rate of New Mexico.

Figure 1.1: Dynamics of Weekly Price of 12 oz Classic Coca Cola in a Grocery Store in Eau Claire, WI

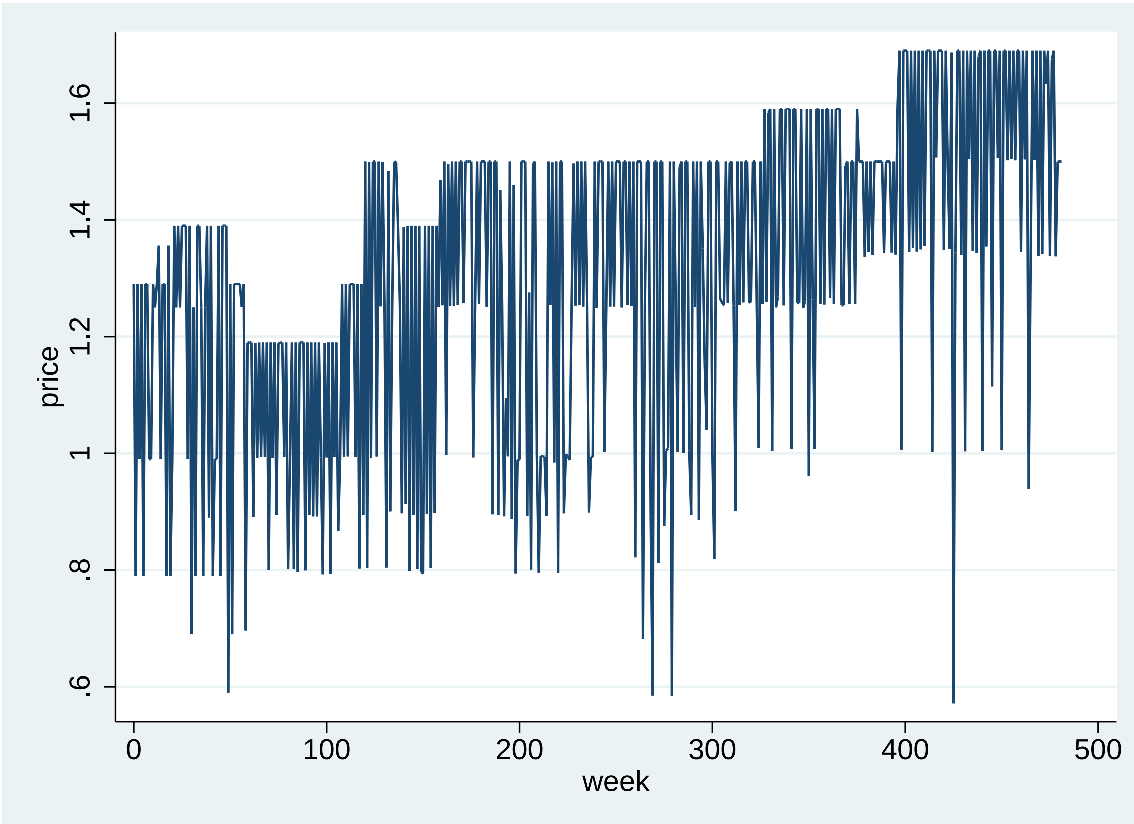

Figure 1.2: Average Price vs Best Price of 12 oz Classic Cola Cola across Stores

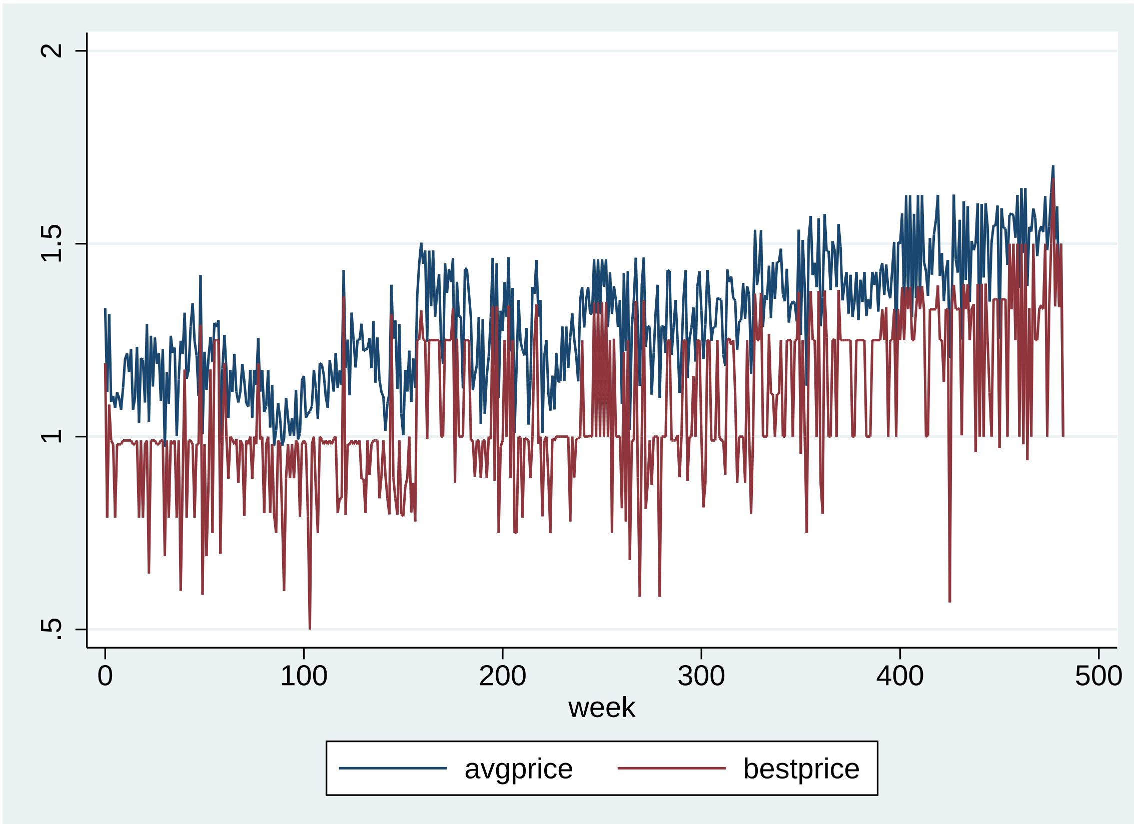

Figure 1.3: Histograms of Bargain Hunting Index for Households in Two Demographic Groups

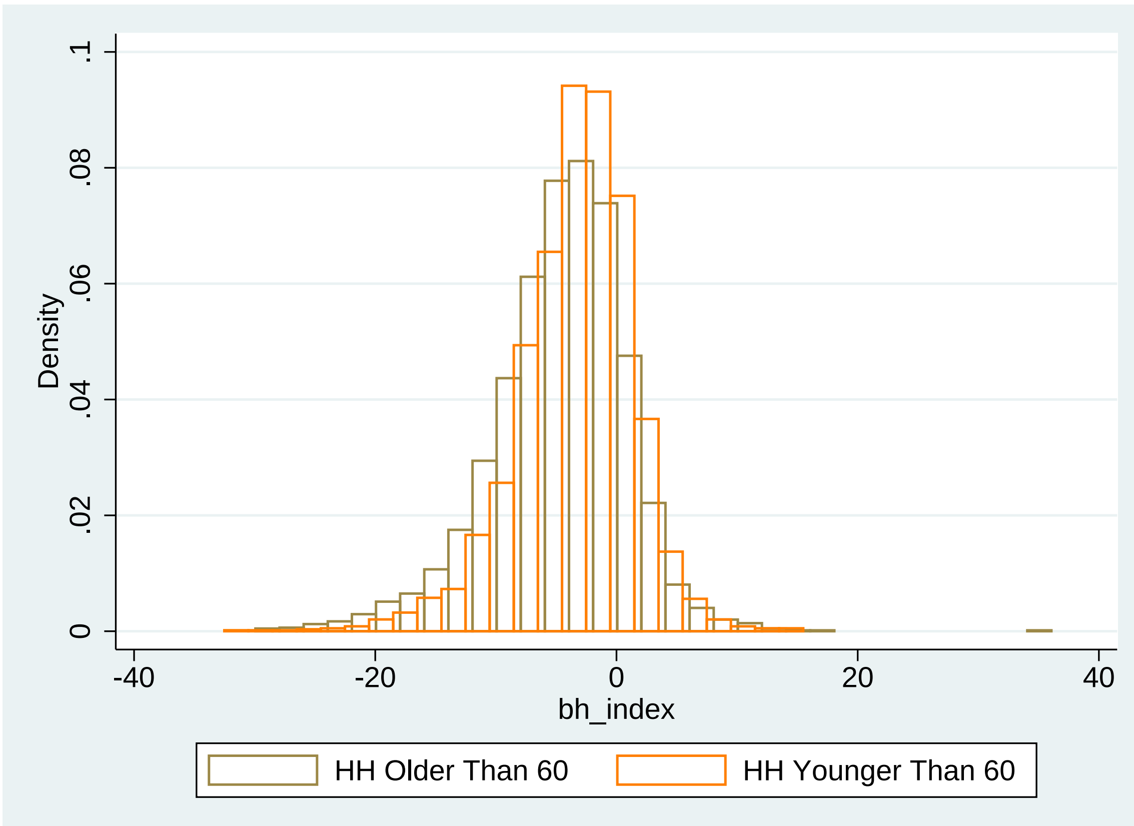

Figure 1.4: Average Number of Product Categories Where A Household Is A Bargain Hunter/Inattentive Consumer

Table 1.3: Effects of Income Shocks on Bargain Hunting Index

Dependent Variable	Bargain Hunting Index	Bargain Hunting Index
Income	0.025	0.026
	(2.01)	(2.10)
Age	-0.011	-0.010
	(-1.78)	(-1.67)
Non-employed	-0.108	1.500
	(-1.10)	(3.74)
Retired	-0.092	-0.387
	(-1.21)	(-1.96)
Unemployment Rate	-0.276	-0.255
	(-9.89)	(-8.49)
Non-employed * UnRate		-0.355
		(-4.14)
Retired * UnRate		0.058
		(1.62)
Year Fixed Effect	YES	YES
Household Fixed Effect	YES	YES
Number of Observations	87098	87098

Note: The results are from the panel regression

$$BHIndex_{i,m,t} = \alpha_i + \eta_t + X_{i,m,t}\beta + U_{m,t}\theta + X_{i,m,t}U_{m,t}\gamma + \varepsilon_{i,m,t}$$

in which i is a household, m is one of the two cities, Pittsfield MA or Eau Claire WI, t is a quarter. α_i is the household fixed effect and η_t is the time fixed effect The bargain hunting index is in percentage. Income is in ten thousands. "Retired" and "Non-employed" are dummy variables, "1" indicating "yes" and "0" indicating "no". Enclosed in the parenthesis are the t-statistics

Table 1.4: Effect of Expenditure on a Product Category and Likelihood of Being a Bargain Hunter for the Category

Dependent Variable	Bargain Hunter	Bargain Hunter
Log Expenditure	0.0924	0.1863
	(7.80)	(13.44)
UnRate * Expenditure	0.0191	-0.0013
	(8.97)	(-0.51)
Retired * Expenditure	-0.0096	-0.0091
	(-1.50)	(-1.40)
Non-employed * Expenditure	-0.0073	-0.0150
	(-0.93)	(-1.90)
Income	0.0006	-0.0018
	(0.86)	(2.32)
Age	0.0049	0.0038
	(19.97)	(14.89)
Non-employed	-0.0217	0.0547
	(-0.67)	(1.67)
Retired	0.0093	0.0446
	(0.37)	(1.74)
UnRate	-0.0103	-0.9232
	(-1.30)	(-58.79)
Category*Year Fixed Effect	No	YES
Number of Observations	719563	715214

Note: The results are from the logit regression

$$BargainHunter_{i,m,c,t} = \alpha_c * \eta_t + log(exp)_{i,m,c,t}\beta + log(exp)_{i,m,c,t}U_{m,t}\gamma + log(exp)_{i,m,c,t}X_{i,m,t}\delta + X_{i,m,t}\phi \ + U_{m,t}\theta + \varepsilon_{i,m,c,t}$$

in which i is a household, m is one of the two cities, Pittsfield MA or Eau Claire WI, c is a product category, t is a year, and X is a vector of demographic variables. α_c is the category fixed effect and η_t is the time fixed effect. "Bargain Hunter" is a binary variable taking on value "1" if the household is a bargain hunter for that category in the year, and value "0" if not a bargain hunter. Income is in ten thousands. "Retired" and "Non-employed" are dummy variables, "1" indicating "yes" and "0" indicating "no". Enclosed in the parenthesis are the z-statistics.

Table 1.5: Effect of Expenditure on a Product Category and Likelihood of Being an Inattentive Consumer for the Category

Dependent Variable	Inattentive Consumer	Inattentive Consumer
Log Expenditure	-0.0031	-0.1327
	(-0.27)	(-9.55)
UnRate * Expenditure	-0.0242	-0.0027
	(-11.34)	(-1.08)
Retired * Expenditure	0.0082	0.0106
	(1.28)	(1.63)
Non-employed * Expenditure	0.0027	0.0146
	(0.35)	(1.84)
Income	-0.000	-0.0014
	(-0.12)	(-1.87)
Age	-0.0047	-0.0038
	(-19.11)	(-14.74)
Non-employed	0.0327	-0.0549
	(1.01)	(-1.66)
Retired	-0.0023	-0.0527
	(-0.09)	(-2.04)
UnRate	0.0407	0.9571
	(5.12)	(60.31)
Category*Year Fixed Effect	No	YES
Number of Observations	719563	715214

Note: The results are from the logit regression

$$InattentiveConsumer_{i,m,c,t} = \alpha_c * \eta_t + log(exp)_{i,m,c,t}\beta + log(exp)_{i,m,c,t}U_{m,t}\gamma + log(exp)_{i,m,c,t}X_{i,m,t}\delta + X_{i,m,t}\phi + U_{m,t}\theta + \varepsilon_{i,m,c,t}$$

in which i is a household, m is one of the two cities, Pittsfield MA or Eau Claire WI, c is a product category, t is a year, and X is a vector of demographic variables. α_c is the category fixed effect and η_t is the time fixed effect. "Inattentive Consumer" is a binary variable taking on value "1" if the household is an inattentive consumer for that category in the year, and value "0" if not an inattentive consumer. Income is in ten thousands. "Retired" and "Non-employed" are dummy variables, "1" indicating "yes" and "0" indicating "no". Enclosed in the parenthesis are the z-statistics.

Table 1.6: Relative Prices as a Function of Unemployment

Dependent Variable	Effective Inflation Rate
Unemp Rate	–0.28 [0.099]**
Observations	3833
categories	31
Category Fix Eff	Yes
Year Dummies	Yes
Std Errors	Unclustered

Note: The table reports estimates of the specification $\pi_{mct} = \beta UR_{mt} + \lambda_t + \theta_c + error$. The sample period is 2001–2011. The dependent variable is the effective inflation rate for a category in a market in a month. First we calculate $\log p_{jmt} - \log p_{jmt-1}$, where j indexes a UPC level product, as the effective inflation rate for each product within a category. Then the effective inflation of a category is the simple average of effective inflation of all products within the category. The prices are deflated by monthly CPI. Thus, the dependent variable is effective inflation based on changes of real prices. Standard errors are in brackets. ***,**,* denote significance at 1%, 5%, and 10% levels.

Table 1.7: Relative Savings as a Function of Unemployment

Dependent Variable	Consumer Savings
Unemp Rate	–1.259 [0.058]***
Family Size	–0.621 [0.103]***
Observations	218348
Households	1673
Household Fix Eff	Yes
Year Dummies	Yes
Std Errors	Unclustered

Note: The table reports estimates of the specification $index_{imt} = \beta \mathrm{UR}_{mt} + \gamma X_{imt} + \text{year dummies} + \theta_i + \text{error}$,. The sample period is 2001–2011.The dependent variable is percentage deviation of actual monthly expenditure from hypothetical monthly expenditure at highest prices for all UPCs the households buy. X_{imt} is a set of household characteristics including the household head's age, education, family size, and combined household income, all of which except family size are categorical variables. For brevity, we only report the coefficient for family size in the table. Standard errors are in brackets. ***,**,* denote significance at 1%, 5%, and 10% levels

Table 1.8: Expenses as a Function of Unemployment

Dependent Variable	Actual Expense
Unemp Rate	–0.027 [0.001]***
Expense at highest price	0.661 [0.001]***
Family Size	–0.014 [0.002]**
Observations	218349
Households	1673
Household Fix Eff	Yes
Year Dummies	Yes
Std Errors	Unclustered

Note: The table reports estimates of the specification $\log Expense_{imt} = \beta_1 \mathrm{UR}_{mt} + \beta_2 \log \bar{Expense}_{mt} + \gamma X_{imt} +$ year effects $+ \theta_i +$ error. The sample period is 2001–2011. The dependent variable is a household's actual monthly expenditure. Hypothetical monthly expenditure at the highest prices household pay for all UPCs bought $\log \bar{Expense}$ is controlled for on the right hand side. The coefficient in interest is β_1, which measures how much the household saves when the local unemployment rate increases by 1%, holding hypothetical expenditure constant. X_{imt} is a set of household characteristics including the household head's age, education, family size, and combined household income, all of which except family size are categorical variables. To compress space we only report the coefficient for family size in the table.Standard errors are in brackets. ***,**,* denote significance at 1%,5%, and 10% levels

Table 1.9: Number of Stores Visited as a Function of Unemployment

Dependent Variable	Number of Stores
Unemp Rate	–0.0125 [0.0012]***
Family Size	0.0087 [0.0021]***
Observations	218349
Households	1673
Household Fix Eff	Yes
Year Dummies	Yes
Std Errors	Unclustered

Note: The table reports estimates of the specification $\log Nstores_{imt} = \beta \mathrm{UR}_{mt} + \gamma X_{imt} + \text{year dummies} + \theta_i + \text{error}$. The sample period is 2001–2011. The dependent variable is the natural logarithm of the number of stores a household visits in a month. X_{imt} is a set of household characteristics including the household head's age, education, family size, and combined household income, all of which except family size are categorical variables. For brevity, we only report the coefficient for family size in the table. Standard errors are in brackets. ***,**,* denote significance at 1%,5%, and 10% levels

Table 1.10: Number of Shopping Trips as a Function of Unemployment

Dependent Variable	Number of Trips
Unemp Rate	0.0327 [0.0022]***
Observations	79618
Households	1673
Household Fix Eff	Yes
Year Dummies	Yes
Std Errors	Unclustered

Note: The table reports estimates of the specification $\log Ntrips_{imt} = \beta \mathrm{UR}_{mt} + \text{year dummies} + \theta_i + \text{error}$. The dependent variable is the natural logarithm of the number of shopping trips a household makes in a month, from 2008 to 2011. Since households are surveyed only once during this period, household characteristics are absorbed into the household fixed effects. Standard errors are in brackets. ***,**,* denote significance at 1%, 5%, and 10% levels

Table 1.11: Heterogeneity in Income and Effects on Relative Savings

Dependent Variable	Consumer Savings	Dependent Variable	Consumer Savings
Unemp Rate	–1.101	Edu1	–0.775
	[0.080]***		[0.265]***
UR× Incq2	–0.173	Edu2	–2.692
	[0.083]**		[1.202]**
UR× Incq3	–0.235	Edu3	3.193
	[0.121]**		[0.693]***
UR× Incq4	–0.004	Edu4	–2.529
	[0.098]		[0.487]***
UR× Incq5	—0.254	Edu5	-2.836
	[0.093]***		[0.413]***
Incq2	1.191	Edu6	–2.931
	[0.517]***		[0.406]***
Incq3	1.380	Edu7	–3.123
	[0.702]***		[0.354]***
Incq4	0.175	Edu8	–0.687
	[0.618]***		[0.421]***
Incq5	0.916	Family Size	–0.637
	[0.625]***		[0.102]***
MaleAge1	8.820	Observations	214604
	[4.210]**	Households	1672
MaleAge2	4.677	Household Fix Eff	No
	[3.705]	Year Dummies	Yes
MaleAge3	8.406	Std Errors	Unclustered
	[3.597]**		
MaleAge4	8.921		
	[3.586]**		
MaleAge5	8.420		
	[3.585]**		
MaleAge6	7.982		
	[3.585]**		

Notes: The table reports estimates of the specification $index_{imt} = \beta UR_{mt} + \sum \gamma_k UR_{mt} \times inc_k + \lambda_t + \theta X_{it} + error$. The sample period is 2001–2011.The dependent variable is percentage deviation of actual monthly expenditure from hypothetical monthly expenditure at highest prices for all UPCs the households buy. X_{it} is a set of household characteristics including the male house head's age, education, occupation, family size, and combined household income, all of which except family size are categorical variables. Definition of dummy variables: (1) incq1=1 if income is within [0, $24,999]; incq2=1 if [$25,000, $44,999]; incq3=1 if [$45,000,$54,999]; incq4=1 if [$55,000,$74,999]; incq5=1 if greater than $75,000. Cumulative shares for each of these approximate quintiles are 19.76, 47.60, 60.33, 79.54, 100 respectively. (2) MaleAge1=1 if age is within [18,24]; MaleAge2=1 if [25,34]; MaleAge3=1 if [35,44]; MaleAge4=1 if [45,54]; MaleAge5=1 if [55,64]; MaleAge6=1 if greater than 65; MaleAge7=1 if "no such person". ***,**,* denote significance at 1%,5%, and 10% levels

Chapter 2

Channels of Wage Income Smoothing: United States 1963-2010

2.1 Introduction

Wage income is the largest component of total compensation in all major advanced economies. In the Great Recession and the following recovery in the United States, total wage income moves together with Gross Domestic Product (GDP), with variation across states. What is the degree of wage income smoothing at the state level? What are the channels through which wage income smoothing is achieved, and their respective contribution? Is the wage income smoothing symmetric across recessions and expansions? To shed light on these issues, I study the patterns of wage income smoothing among U.S. states during the period 1963-2010. There are three channels that wage income smoothing can occur in a federal regime and a single market for labor: net taxes, employers, and interstate commuting. First, federal and local governments can reduce their shares of Gross Domestic Products by reducing taxes imposed on firms, and thus boosting the share of total compensation for labor and capital. Second, through labor contracts, employers can maintain the level of wage income across business cycle. Third, in a single market for labor, workers can commute to work in other states that have better job prospects.

Following the framework in Asdrubali, Sorensen and Yosha (1996), I quantify the amount of state-level wage income smoothing at each of these levels of smoothing in the United States. This methodology gives a decomposition of a the cross-sectional variance in gross state product and yields the following identity:

$$1 = \beta_T + \beta_E + \beta_C + \beta_U,$$

where β_T, β_E, β_C are the fractions of shocks to gross state product smoothed by net taxes, employers, and interstate commuting income, and β_U is the fraction of shocks that are not smoothed. My main objective is to estimate the components of this relationship. For the period 1963-2010, I find that 1.8 percent of shocks to gross state product are smoothed by net taxes on production, 55.1 percent are smoothed by employers, and 3 percent are smoothed by interstate commuting income. The remaining 40.1 percent are not smoothed.

I also decompose β_U, the fraction that is not smoothed, into two subcategories: number of employment and average earnings per employment, both of which are procyclical to shocks to gross state product, but average earning per employment is more insulated from shocks than the total compensation from employment. Employers can lay off workers but maintain the pay level for those who keep the job. Put in a different way, unemployment is a shock absorber that smooths the average earnings per employment. I find that unemployment smooths 22.3 percent of shocks to total compensation.

Next, I study how wage income smoothing vary across four non-overlapping time periods, 1963-1973, 1974-1983, 1984-2003, 2004-2010. What stands out is the decade 1974-1983, for which employers smoothed the least fraction of shocks and largest fraction of shocks were passed through to labor compensation in the four sub-periods.

Lastly, I study the speed of adjustment of wage income to economic expansions and recessions. The asymmetrical pattern of adjustment is termed "rockets and feathers", referring to the fact that prices of downstream products respond faster and more strongly to positive shocks to upstream prices than negative ones. I test whether the adjust of wage income exhibit such a feature.

The rest of the paper is organized as follows. Section 2 is the literature review. Section 3 is a theoretical framework of risk-sharing contracts with and without worker's mobility. Section 4 is definition of variables and the variance decomposition framework. Results are presented in Section 5. Section 6 is the conclusion.

2.2 Literature Review

My work is related to four strands of literature. The first is on risk-sharing of personal income and consumption over the business cycle. The second is on real wage rigidity over the business cycle. The third is risk-sharing implicit contract models. The fourth is regional labor market adjustment to shocks. In this section I will briefly discuss representative papers in each strand and my contribution to the literature.

Asdrubali, Sorensen and Yosha (1996)(hereafter ASY 1996) develop a framework for quantifying the amount of risk sharing among states of the U.S. and decompose it into several contributing channels. Following this framework, several papers study the extent of regional risk sharing in different countries and suggest new channels of income and consumption smoothing.

Borge and Matsen (2004) analyze public employment as a risk sharing channel in Norway over the period 1977-1990. They find it smooths up to 25% private sector output shocks. Demyanyk, Ostergaard, and Sorensen (2007) investigate how bank lending to small businesses smooths state-level personal income. Juessen (2008) focuses commuting as a risk-sharing channel for consumption at state-level. Hoffmann and Shcherbakova (2011) look into the business cycle angle of consumption risk sharing and find it is pro-cyclical. These papers estimate the extent of risk sharing for personal income and consumption, but they do not decompose it to separate components of personal income. In my knowledge, there is no study on risk sharing of wage income, the largest component of personal income in most advanced economies. This paper tries to fill this gap in the literature.

The study of real wage over the business cycle can date back at least to Keynes (1936), in which he wrote "...in general, an increase in employment can only occur to the accompaniment of a decline in the rate of real wages." Abraham and Haltiwanger (1995) provide an excellent review of this literature on early evidence of cyclicality of real wages. On one hand, real wages being countercyclical, as conjectured by Keynes, is consistent with theories of sticky nominal wages and sticky expectations. On the other hand, real wage procyclicality is also consistent with alternative workhorse macroeconomic theories such as real business cycle models. In the early papers (Bodkin 1969, Otani 1978, Chirinko 1980, and Sumner and Silver 1989), in typical regressions, levels or growth rates of annual aggregate hourly earnings are regressed against annual unemployment rate to study the real wage behavior over the business cycle. Findings are mixed. Results are sensitive to a number of measurement choices: (1)how to construct the real wage; (2) how to measure the cyclical indicator; (3) how to detrend data; (4)the frequency and sample period of data; (5)how to control for industry composition over time; (6)how to control for workforce composition over the cycle. Over the last two decades, with access to micro panel data in the United States to overcome the issues listed above, many studies (see Shin 1994; Solon, Barsky and Parker 1994 and Devereax 2001) come to the consensus that real wages are procyclical. Unlike these researches using either national aggregate data or micro panel data, my work is based on state level data, which allows for more cross-sectional variation, comparing to nationally aggregate data, and decomposition of smoothing of wage income at the state level into several "macro" channels.

The literature of risk-sharing contract models dates back to Azariadis (1975) and

Bailey (1974). They show that in an economy of risk-neutral firms and risk-averse workers, a binding insurance labor contract is a welfare improvement, and under such a contract, real earnings are invariant to idiosyncratic shocks. Harris and Holmstrom (1982) and Thomas and Worrall (1988) extend their models to allow for the contract non-binding to either party. Beaudry and DiNardo (1991)develop nested models linking wages to labor market conditions to test the relative importance of spot market and implicit contracts in determining real wages. I use a simplified version of their models as the theoretical underpinning of empirical analysis in this paper.

Blanchard and Katz (1992) establish stylized facts about how states in the U.S. respond to regional shocks in terms of adjustment in unemployment, participation and interstate migration in the post-war period up to 1990. They conclude that interstate migration plays the most important role for adjustments to regional shocks, more so than regional relative wages or firm reallocation. A recent paper by Dao, Furceri and Loungani (2014) provide updated facts on regional labor market adjustments. Among other findings, the extent of absorbing regional shocks by labor participation rates increases over time. This paper continues this vein of research and provide new facts of firms adjusting employment versus wages to regional shocks.

2.3 Theoretical Framework of Risk-Sharing Contract

I present in this section a risk-sharing contract framework, a simplified version of Beaudry and DiNardo (1991), to account for the real wage rigidity in the business cycle. There are three nested wage-setting models: a spot market, in which wage is determined by each period's productivity shock ; a full-commitment risk-sharing model, in which the wage for a worker is determined by the productivity shock at the time when the worker was hired; and a full mobility implicit contract model, in which the wage for a worker is determined by the highest productivity shock since employment began.

If all employment is signed in a spot market, according to a neo-classical model where output is determined by a Cobb-Douglas production function, wage income is a fixed portion of aggregate products and thus always moves one-for-one with GDP. In the remaining of this section I will focus on the case when wage is not determined in the spot market.

Consider an economy populated with risk-neutral entrepreneurs and risk-averse workers. The economy produces only one good, and the worker's utility per period associated with the consumption of c units of the good is given by $U(c)$. Both types of agents have a discount factor equal to β. Also assume the labor market is competitive. Each of the entrepreneurs is assumed to have access to a technology that requires one worker. The working hours are fixed throughout the employment. Therefore labor income is in fixed proportion to wage. The quantity of output from this technology is given by $\Phi(t)$, where $\Phi(t)$ represents the state of labor productivity at time t. Assume that the stochastic process of labor productivity is represented in the AR(1) process:

$$\Phi(t) = (1-\alpha)\Phi^* + \alpha\Phi(t-1) + \epsilon(t), 0 < \alpha \leq 1, \epsilon(t) is i.i.d, \tag{2.1}$$

where Φ^* is the long-term level.

When workers do not have access to capital markets, entrepreneurs have incentives to offer employment contracts that protect workers against the risks associated with productivity shocks. Obviously, competition will force such contracts to offer zero expected profits to employers. If both firms and workers can commit to the contract, then in every period the market equilibrium for risk-sharing employment contracts will be the solution to the following program:

$$\begin{aligned} max_{\{\omega_{t+j}\}} \sum_{i=0}^{\infty} \beta^j E_t \left[U(\omega_{t+j})\right] \\ s.t. \quad \sum_{i=0}^{\infty} \beta^j E_t \left[\Phi_{t+j} - \omega_{t+j}\right] = 0. \end{aligned}$$

The solution to this problem is simply that the wage paid at time $t+j$ in a contract negotiated at time t is:

$$\omega(t+j,t) = \Phi_* + \frac{1-\beta}{1-\alpha\beta}\left[\Phi(t) - \Phi^*\right] \tag{2.2}$$

The wage throughout the employment depends only on the productivity level at time t and is independent of j. Its implications are twofold. First, wage responds to current technology shock only and more than one-for-one. Second, once a contract is signed, wage does not respond to future productivity shocks or total income.

Given this process for the contractual wages, employment will adjust such that the marginal worker will be indifferent between accepting a job today and staying unemployed this period and postponing until next period the decision to take a job. When workers are unemployed, they are assumed to receive a reservation wage denoted $\bar{\omega}$, which could be from social insurance and/or home production. The reservation wage can be agent-specific. The equilibrium condition related to this indifference relationship is given by:

$$U(\bar{\omega}) + \beta E[\frac{V(\omega(t+1,t+1),\Phi(t+1))}{\Phi(t)}] = V(\omega(t,t),\Phi(t)). \tag{2.3}$$

The expression $V(\omega, \Phi(t))$ represents the discounted expected utility associated with having a job with the contract wage equal to ω when the state of technology is $\Phi(t)$.

Equation (3) states that the expected discounted value of staying unemployed today, receiving $\bar{\omega}$ and accepting a job tomorrow must be equal to the value of accepting a job today.

use equations (1)-(3) to solve for equilibrium relationship between the contract wage and the reservation wage. Assume a logarithm utility function, we can derive for the relationship:

$$log[\omega(t+j,t)] = \frac{1}{1-\beta}[\beta(1-\alpha)log(\Phi^*) + \beta Rp] + \frac{1-\beta}{1-\alpha\beta}log[\omega h(t)] \tag{2.4}$$

where Rp is the residual representing second-order and higher terms. It is always negative because $U(.)$ is concave and assumed constant.

Equation (4) states that the time $(t+j)$-period wage paid to worker who began his job at time t depends positively on the reservation wage of the marginal worker employed at time t. Given the general equilibrium nature of the problem, this reservation wage represents the marginal value of household production and therefore should be negatively related to the fraction of workers remaining in that sector. Consequently, it is reasonable to assume that the reservation wage of the marginal worker changes with the participation rate, $l(t)/L(t)$, as given by:

$$ln[\omega h(t)] - ln[\omega H(t-1)] = \frac{(1-\theta)[l(t) - l(t-1)]}{L(t)}, \quad 0 < \theta < 1 \qquad (2.5)$$

Substituting equation (5) into equation (4) results in

$$log[\omega(t+j,t)] = \Omega_1 + \Omega_2\big[1 - \frac{l(t)}{L(t)}\big], \qquad (2.6)$$

where

$$\Omega_1 = \frac{1}{1-\beta}[\beta(1-\alpha)log(\Phi^*) + \beta Rp]$$

$$\Omega_2 = \frac{-(1-\theta)(1-\beta)}{1-\alpha\beta} < 0$$

. The implication of equation (6) is that when there is a positive productivity shock to the economy, workers entering employment sign new long-term contracts that reflect their current marginal product. However this shock does not affect wages of workers who entered in previous periods. Therefore the sensitivity of total labor income to productivity shocks is less than one.

Extension to Risk-sharing Contracts with Mobile Workers

One of the assumptions used to derive equation (6) is that workers can commit not to quit a job even though employment contracts offered on the market may be better than the one at hand. We shall call such a situation the case of limited labor mobility. However, when job mobility is costless for workers, the only feasible contracts to which they can commit themselves are those in which it is never profitable for another employer to bid them away. Therefore, contracts must render non-positive expected profits for the employer in every period and in every state (otherwise the workers will be bid away). The conditions imposed on a contract in order to satisfy the absence of "bidding-away" opportunities are given by the following inequalities:

$$E\big[\sum_{i=j}^{\infty}\beta^{i-j}[\Phi_{t+i}-W_{t+i}(\Phi_{t_i})|\Phi_{t+j}]\big]\leq 0 \tag{2.7}$$

for all $j=1,...\infty$ and all realizations of Φ^{t+j}.

In the inequality (7), the wage $W_{t+j}(\Phi^{t+j})$ represents the wage paid in period $t+j$ after a history of productivity shocks $\Phi^{t+j}=(\Phi_t,\Phi_{t+1},...,\Phi_{t+j})$ and for a job that began at time t.

Harris and Holmstrom (1982) give a solution to a problem very close the one above, only with the difference that the time horizon is finite in their paper. The optimal zero-profit risk-sharing contract satisfying the non-bidding-away constraints is given by:

$$W_{t+j}(\Phi^{t+j})=max\{W_{t+j-1},X(\Phi_{t+j})\}=max\{X(\Phi_{t+i})\}_{i=1}^{j} \tag{2.8}$$

The function $X(\Phi_{t+i})$ represents the initial wage paid in a contract negotiated in state Φ_{t+i} and is equal to the average expected productivity conditional on $\{\Phi_{t+i},...|\Phi_t$

being below Φ_t since any realizations of Φ_t must give zero expected profits. The wage contract defined by equation (8) is often referred to as a downwardly rigid contract. Under such a contract, a worker's wage is adjusted to match the contemporaneously negotiated first-period wage $X(\Phi_{t+j})$, whenever the latter is above the former. This adjustment is undertaken so that workers do not quit because of higher wages offered elsewhere.

I now move on to model the relation between predicted wage with observed labor market conditions. As in the case of no mobility, it is assumed that the reservation wage is negatively related to the unemployment rate, the market equilibrium is:

$$W_{t+j}(\Phi^{t+j}) = W(t+j,t) = max\big\{k\big[1 - \frac{l(t+i)}{L(t+i)}\big]\big\}_{i=0}^{j}, \quad k^{'}(.) < 0, \tag{2.9}$$

where $k(.)$ is a function of unemployment rate.

The implications of equation (8) and (9) are twofold. First, as worker's mobility increases over time, the wage income would be more responsive to productivity shocks. Second, asymmetric responses to positive and negative shocks are allowed. Wages increase when shocks are positive while stay the same for negative shocks.

In the later sections I will test the implications from the three nested models.

2.4 Decomposition of Variance in Gross State Product

Here is the identity linking up gross state product and wage income:

$$GSP_i = \frac{GSP_i}{GSP_i - NT_i} \frac{GSP_i - NT_i}{WagePW_i} \frac{WagePW_i}{WageR_i} WageR_i \tag{2.10}$$

The variables in the equation are described below.

Gross state product (GSP). Using the income method, GSP is the sum of compensation of employees, net taxes on production and imports and gross operating surplus.

Gross operating surplus. Defined as the income derived from production by incorporated enterprises that is earned by the capital factor.

Net taxes (NT). Defined as taxes on production and import minus subsidies. Roughly speaking, compensation of employees is labor's share of a state's output, gross operating surplus is capital's share, and net taxes is the government's share.

Wages and salaries are broadly defined to include commissions, tips, and bonuses; voluntary employee contributions to deferred compensation plans, such as 401(k) plans; employee gains from exercising stock options; and receipts-in-kind that represent income. Wage and salary disbursements are measured before deductions, such as social security contributions, union dues, and voluntary employee contributions to defined contribution pension plans. The difference between Wage and salary disbursement by place of work ($WagePW$) is the interstate commuting income.

Taking logs and differences of Equation (10), multiplying both sides by $\Delta \log(GSP_i)$, we obtain the following decomposition of the cross-sectional variance in GSP:

$$
\begin{aligned}
var\{\Delta \log(GSP)\} =& cov\{\Delta \log(GSP),\ \Delta \log(GSP) - \Delta \log(GSP - NT)\} \\
&+ cov\{\Delta \log(GSP),\ \Delta \log(GSP - NT) - \Delta \log(WagePW)\} \\
&+ cov\{\Delta \log(GSP),\ \Delta \log(WagePW) - \Delta \log(WageR)\} \\
&+ cov\{\Delta \log(GSP),\ \Delta \log(WageR)\}
\end{aligned}
\tag{2.11}
$$

Divided by the variance of $\Delta \log(GSP)$ to get:

$$1 = \beta_T + \beta_E + \beta_C + \beta_U \tag{2.12}$$

where β_T is the OLS estimate of the slope in the regression of $\Delta \log(GSP) - \Delta \log(GSP - NT)$ on $\Delta \log(GSP)$, β_E is the OLS estimate of the slope in the regression of $\Delta \log(GSP - NT) - \Delta \log(WagePW)$ on $\Delta \log(GSP)$, β_C is the OLS estimate of the slope in the regression of $\Delta \log(WagePW) - \Delta \log(WageR)$ on $\Delta \log(GSP)$, β_T is the OLS estimate of the slope in the regression of $\Delta \log(WageR)$ on $\Delta \log(GSP)$.

Actual regressions to estimate the four coefficients are:

$$
\begin{aligned}
\overline{\Delta \log(GSP_{i,t})} - \overline{\Delta \log(GSP_{i,t} - NT_{i,t})_{i,t}} =& \mu_i + \nu_{T,t} + \beta_T \overline{\Delta \log(GSP_{i,t})} + \varepsilon_{i,T,t} \\
\overline{\Delta \log(GSP_{i,t} - NT_{i,t})} - \overline{\Delta \log(WagePW_{i,t})} =& \mu_i + \nu_{E,t} + \beta_E \overline{\Delta \log(GSP_{i,t})} + \varepsilon_{i,E,t} \\
\overline{\Delta \log(WagePW_{i,t})} - \overline{\Delta \log(WageR_{i,t})} =& \mu_i + \nu_{C,t} + \beta_C \overline{\Delta \log(GSP_{i,t})} + \varepsilon_{i,C,t} \\
\overline{\Delta \log(WageR_{i,t})} =& \mu_i + \nu_{U,t} + \beta_U \overline{\Delta \log(GSP_{i,t})} + \varepsilon_{i,U,t}
\end{aligned}
$$

where $\overline{\Delta \log(GSP_{i,t})}$ is the idiosyncratic growth rate of a state in a year, defined as $\overline{\Delta \log(GSP_{i,t})} = \Delta \log(GSP_{i,t}) - \overline{\Delta \log(GSP_{i.})} - \overline{\Delta \log(GSP_{.t})}$, where $\overline{\Delta \log(GSP_{i.})}$ is the average growth rate of GSP for a state in all years in the sample and $\overline{\Delta \log(GSP_{.t})}$ is the average growth rate of GSP for all states in a year. $\nu_{.,t}$ are time fixed effects. The β coefficients will be weighted averages of the year-by-year cross-sectional regressions. The time fixed effects capture year-specific impacts on nation-wide growth rates such as shocks to Gross Domestic Product.

The variance of the data series vary significantly across states due to the fact that shocks to some states are more volatile more those to other states. Following the two-step procedure in ASY (1996) to correct for heteroskedasticity. In the first step I run a panel Ordinary Least Square (OLS) estimation. For the residuals I estimate the variance of the error terms in the regression assuming that it varies by state. In the second step the variables are weighted by the estimated standard error for the state.

2.5 Results

Table 1 is the main results. 40.1 percent of shocks to gross state product are not smoothed. The estimated standard error indicates it is statistically significant. This finding is consistent with the real wage rigidity literature and evidence against the spot market model.

Decomposition of wage income smoothing show a significant part of shocks to gross state product is absorbed by employer. I interpret it as employers maintain the wage income of their employees. The amount of smoothing accomplished by net taxes is 1.8 percent and that smoothed by interstate commuting is 3 percent. The total amount of smoothing through the three channels is 59.9 percent.

Further Channel of Wage Income Smoothing

Next I further decompose the amount of shocks to gross state products into two parts:wage income per capita can be further smoothed by higher unemployment rate. Note the identity of wage income per capita:

$$Wage\, per\, capita = \frac{Total\ Wage\ and\ Salary}{Population} = \frac{Total\ Wage\ and\ Salary}{Employment}\frac{Employment}{Population} \tag{2.13}$$

I suppress the subscripts of year and state. By regressing the two components separately against gross state product, the unsmoothed shocks to wage and salary are decomposed into two parts: those smoothed by higher unemployment rates and shocks to wage per employed worker that are still not smoothed.

Table 2 shows the results for the new decomposition. Results for the three channels, net taxes, employers and interstate commuting, are the same as in Table 1. The amount of smoothing of wage income per employed worker is 22.3 percent, while the unsmoothed shocks to wage income per employed worker is 20.1 percent.

Subperiods

An interesting question is to check if the accomplished smoothing by each channel is stable over time. Given that length of times series (48 years) I split the time series of data into five subperiods.

The results are reported in Table 3. The shocks to gross state products absorbed by each channel changed considerably over the five subperiods. The period 1974-1983 is abnormal compared to other subperiods, when the shares of wage income smoothing attributed to each channel are relatively stable. Notably employers smooth around two-thirds of shocks in all the five periods except in the period 1974-1983.

Different Frequency of Data If wage income smoothing is affected not only by contemporaneous shocks to gross state product but also lagged shocks, then the variance decomposition framework captures only part of the wage income smoothing actually achieved. To test this I take difference of data at different frequencies–k-differenced data means adjacent observations are k years apart. The amount of wage income smoothing via each channel is stable across differing frequencies. The main effect is that shocks to GSP that are not smoothed increase significantly, which is largely due to smoothing by employers drops by around 20%. This may reflect the fact that employers do not commit to the size of payroll for long if states are hit by negative shocks several years in a row.

Lag Adjustment of Wage Income to GSP Shocks The adjustment of wage income to GSP shocks may not be instantaneous or symmetric. Due to the fact that typical labor contracts are signed for multiple years, employers can adjust the pay level of their workforce gradually. Borenstein, Cameron and Gilbert (1997) test the the asymmetrical response of gasoline prices to crude oil price changes. Similarly I model asymmetric responses of wage income growth to GSP shocks as follows:

$$\begin{aligned} \overline{\Delta\log(Wage_{i,t})} &= \beta_0^+\overline{\Delta\log(GSP_{i,t})} \\ \overline{\Delta\log(Wage_{i,t+1})} &= \beta_1^+\overline{\Delta\log(GSP_{i,t})} \\ & \\ \overline{\Delta\log(Wage_{i,t+n})} &= \beta_n^+\overline{\Delta\log(GSP_{i,t})} \end{aligned} \tag{2.14}$$

if $\overline{\Delta\log(GSP_{i,t})} > 0$, and

$$\begin{aligned} \overline{\Delta\log(Wage_{i,t})} &= \beta_0^-\overline{\Delta\log(GSP_{i,t})} \\ \overline{\Delta\log(Wage_{i,t+1})} &= \beta_1^-\overline{\Delta\log(GSP_{i,t})} \\ & \\ \overline{\Delta\log(Wage_{i,t+n})} &= \beta_n^-\overline{\Delta\log(GSP_{i,t})} \end{aligned} \tag{2.15}$$

if $\overline{\Delta\log(GSP_{i,t})} < 0$. Also define

$$\begin{aligned} \overline{\Delta\log(GSP_{i,t})}^+ &= max\big(\overline{\Delta\log(GSP_{i,t})}, 0\big) \\ \overline{\Delta\log(GSP_{i,t})}^- &= min\big(\overline{\Delta\log(GSP_{i,t})}, 0\big). \end{aligned} \tag{2.16}$$

A simple empirical model that allows for asymmetric adjustment can be written

$$\overline{\Delta\log(Wage_{i,t})} = \sum_{i=0}^{n}\left(\beta_i^+\overline{\Delta\log(GSP_{i,t-i})}^+ + \beta_i^-\overline{\Delta\log(GSP_{i,t-i})}^-\right) + \varepsilon_{it}, \tag{2.17}$$

where ε is assumed to be an *iid* error term.

Results are shown in Table 5 and Table 6. Comparing the two tables, it is easy to see that responses of wage income to positive and negative GSP shocks are different. For 1 percent positive shock to the idiosyncratic growth rate of GSP in a state, the response of same year idiosyncratic growth rate of wage income is 0.324 percent, while for 1 percent negative shock it is -0.401 percent. The accumulative change after three years for the former is 0.40 percent whereas -0.704 percent for the latter. In other words, wage income responds stronger and faster to negative GSP shocks than positive ones, which is a reversed "rockets and feathers" feature. This finding does not lend support to the mobility risk-sharing contract model.

2.6 Conclusion

I find that a considerable amount of shocks to GSP are smoothed via the three channels: net taxes, employer and interstate commuting. They smooth 1.8%, 55.1% and 3.0%, respectively, of shocks to GSP. Employers are the most important shock absorber. By further decomposing the unsmoothed shocks, I find that unemployment is another channel of smoothing wage income of employed workers. Shocks to wage income per capita that are not smoothed are 40.1%, whereas only 20.1% of shocks to wage income per employer worker are not smoothed. This pattern of wage income smoothing is persistent in all five subperiods except the period 1974-1983. It is also robust to different frequencies of data. Finally, I find that there is reversed "rockets and feather" feature in smoothing shocks to GSP. Wage income responds stronger and faster to negative shocks to GSP.

It would be interesting to further explore the heterogeneity in wage income smoothing. How much of the wage income smoothing is achieved by top earners versus average earners, especially over the business cycle? Do the two groups of workers exhibit different dynamics and sensitivities to positive economic shocks when top earners enjoy higher mobility and can easily find more favorable job offers. These questions cannot be answered using state level aggregate data. Combining firm-level wage survey and macro data may shed more light on these questions.

Figure 2.1: Idiosyncratic Growth Rates of GSP and Wage Income in Alaska

Figure 2.2: Idiosyncratic Growth Rates of GSP and Wage Income in New York

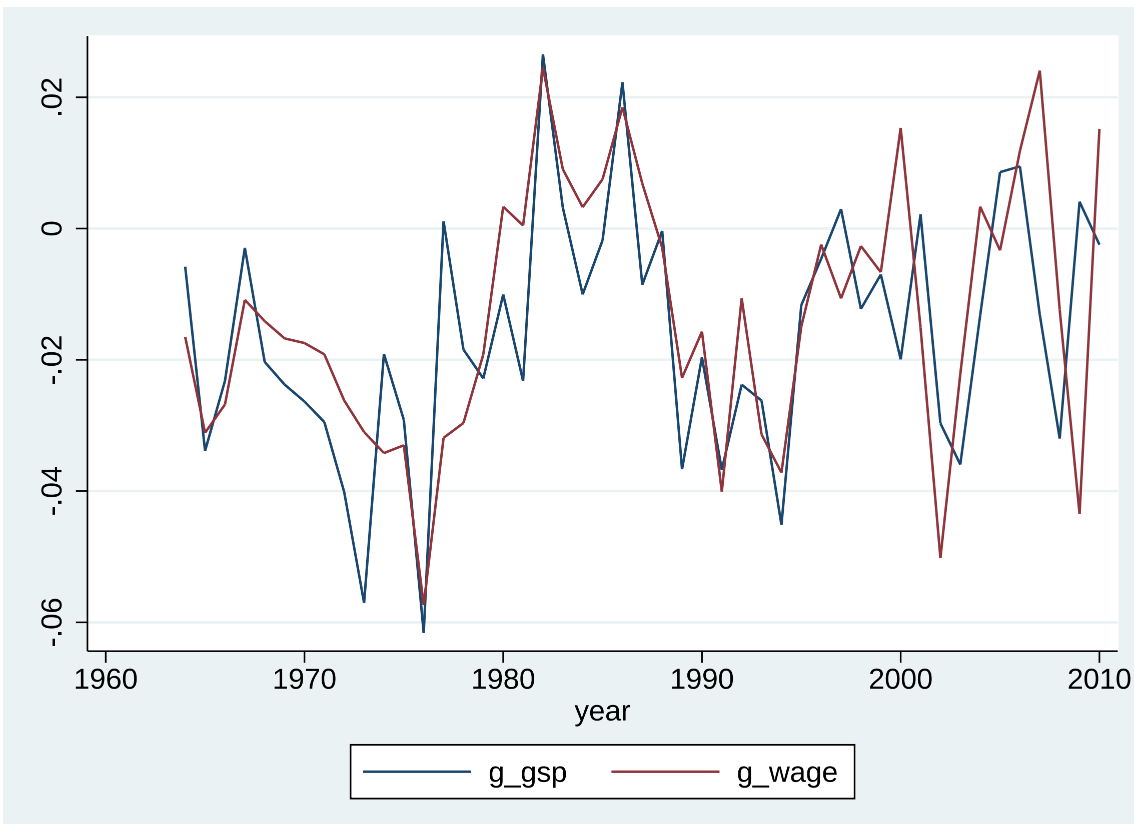

Figure 2.3: Idiosyncratic Growth Rates of GSP and Wage Income in Texas

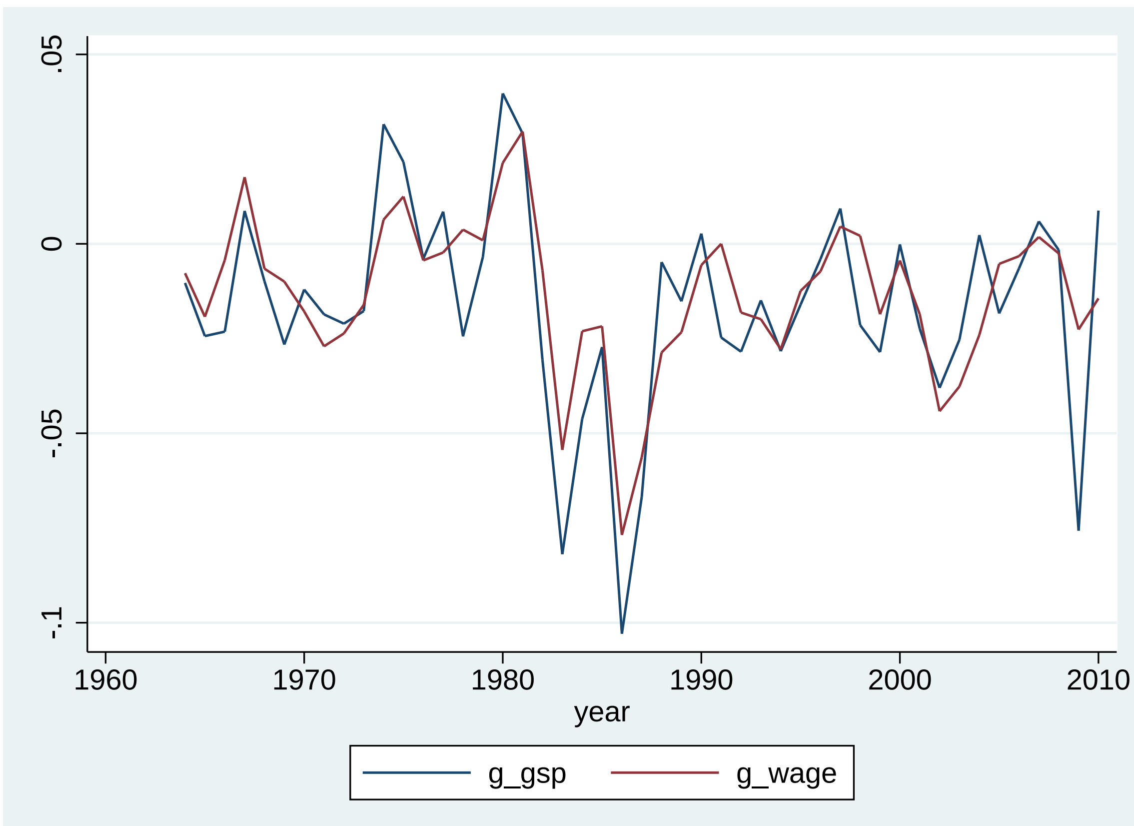

Table 2.1: Channels of Wage Income Smoothing (Percent)

Net Taxes (β_T)	1.8
	(0.4)
Employer (β_E)	55.1
	(1.2)
Interstate Commuting (β_C)	3.0
	(0.4)
Not Smoothed (β_U)	40.1
	(1.1)

Notes: Percentages of shocks to gross state product absorbed at each level of smoothing. Standard errors are in parentheses.

Table 2.2: Smoothing of Employed Workers' Wage Income by Unemployment Rate

Net Taxes (β_T)	1.8
	(0.4)
Employer (β_E)	55.1
	(1.2)
Interstate Commuting (β_C)	3.0
	(0.4)
Unemployment (β_{UR})	22.3
	(0.8)
Not Smoothed (β_U)	20.1
	(0.8)

Notes: Percentages of shocks to gross state product absorbed at each level of smoothing. Standard errors are in parentheses.

Table 2.3: Channels of Wage Income Smoothing in Five Decades (Percent)

Channel	1964-1973	1974-1983	1984-1993	1994-2003	2004-2010
Net Taxes (β_T)	-1.3	9.2	-6.5	4.4	6.3
Employer (β_E)	64.8	35.5	70.0	74.1	64.8
Interstate Commuting (β_C)	1.2	7.0	0.7	0.9	0.3
Not Smoothed (β_U)	35.3	48.2	35.8	29.4	28.8

Notes: Percentages of shocks to gross state product absorbed at each level of smoothing in five subperiods. Standard errors are in parentheses.

Table 2.4: Channels of Wage Income Smoothing, Different Frequencies

Channel	3-year Lag	5-year Lag	10-year Lag
Net Taxes (β_T)	3.95	3.93	3.94
	(0.34)	(0.31)	(0.27)
Employer (β_E)	35.87	34.55	34.7
	(1.10)	(0.99)	(0.91)
Interstate Commuting (β_C)	3.19	2.24	3.46
	(0.33)	(0.31)	(0.27)
Not Smoothed (β_U)	56.99	59.28	57.93
	(1.03)	(0.97)	(0.90)

Notes: Percentages of shocks to gross state product absorbed at each level of smoothing. Standard errors are in parentheses.

Table 2.5: Lag Adjustment of Wage Income Smoothing

Dependent Variables	Reg 1	Reg 2
ΔGSP_0	0.383	0.359
	(0.031)	(0.037)
ΔGSP_1	0.238	0.106
	(0.012)	(0.025)
ΔGSP_2	0.035	0.013
	(0.019)	(0.032)
ΔGSP_3	-0.059	-0.017
	(0.043)	(0.036)
$\Delta Wage_1$		0.370
		(0.103)
$\Delta Wage_2$		-0.158
		(0.050)
$\Delta Wage_3$		-0.034
		(0.030)
Time Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Observations	2200	2200
R^2	0.515	0.580

Notes:. Robust standard errors are in parentheses.

Table 2.6: Asymmetric Lag Adjustment of Wage Income Smoothing

Dependent Variables	Reg 1	Reg 2
ΔGSP_0^+	0.324	0.317
	(0.115)	(0.111)
ΔGSP_1^+	0.232	0.100
	(0.025)	(0.070)
ΔGSP_2^+	-0.032	-0.071
	(0.066)	(0.076)
ΔGSP_3^+	-0.152	-0.082
	(0.088)	(0.051)
ΔGSP_0^-	0.401	0.363
	(0.081)	(0.092)
ΔGSP_1^-	0.234	0.112
	(0.011)	(0.013)
ΔGSP_2^-	0.076	0.064
	(0.019)	(0.018)
ΔGSP_3^-	-0.007	0.028
	(0.020)	(0.031)
$\Delta Wage_1$		0.360
		(0.107)
$\Delta Wage_2$		-0.159
		(0.040)
$\Delta Wage_3$		-0.050
		(0.028)
Time Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Observations	2200	2200
R^2	0.515	0.581

Notes:. Robust standard errors are in parentheses.

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